Non-Cognitive Abilities and Loan Delinquency*

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January 2014

Abstract

Research on household financial decisions has largely focused on the importance of cognitive abilities in decision-making, emphasizing for example that IQ and math ability predict stock market participation and the avoidance of financial mistakes. This paper takes a broader perspective by exploring the role of non-cognitive abilities in household borrowing and default decisions. Within the fields of labor and education economics, non-cognitive traits such as self-efficacy – the perceived ability to control one's future outcomes – predict substantial differences in school achievement and employment outcomes. Using longitudinal household survey data, we show that an individual's self-efficacy during childhood also predicts differences in future delinquency on debt and bill payments. The effect of self-efficacy on delinquency is both substantial and robust; a one standard deviation increase in self-efficacy corresponds to a 15-20% decrease in the likelihood of delinquency, and this effect is not explained by differences in gender, race, cognitive ability, educational attainment and income, contemporaneous or past.

^{*} We thank Tom DeLeire and Lindsey Leininger for helpful comments and discussion. All remaining errors are ours.

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1. Introduction

Recent evidence has identified a substantial degree of heterogeneity across people in their propensity to make financial mistakes (Campbell 2006). A growing body of work in the household finance literature suggests that cognitive abilities are significant drivers of good financial outcomes (e.g., Agarwal and Mazumder 2013). However, non-cognitive abilities are also likely to be useful. Good financial outcomes require planning, motivation and perseverance. A necessary ingredient for these is self-efficacy, which refers to the degree to which people believe that they can influence future outcomes through their effort and choices (Gecas 1989).

Here, we provide evidence that self-efficacy is an important determinant of household financial decisions and outcomes. Specifically, we find that high self-efficacy, measured early in life, predicts the avoidance of delinquency on household debts, including credit card and vehicle loans, even after controlling for differences in cognitive ability, education, income and demographic characteristics.

Our findings complement the existing work showing the importance of cognitive abilities, education and financial literacy for successful financial outcomes. Better cognitive abilities, in particular mathematical knowledge, predict a lower incidence of mortgage delinquency, fewer mistakes in credit card usage and loan choices, and better saving behavior (Gerardi et al. 2013, Agarwal and Mazumder 2013, Stango and Zinman 2009). Individuals with better cognitive ability as measured by IQ tests are more likely to participate in the stock market and earn higher Sharpe ratios (Grinblatt et al. 2011). The decline in cognitive ability induced by age leads to more errors in financial choices (Agarwal et al. 2009). Financial knowledge helps individuals choose better investment

portfolios and plan better for retirement (Lusardi and Mitchell 2009, Choi et al. 2010). Education has beneficial effects on financial market participation and credit management (Campbell 2006; Cole, Shastry and Paulson 2012). We contribute to this line of work in household finance by showing that non-cognitive skills, in particular people's capacity to believe that they can influence their future, are also helpful for achieving good financial outcomes in life.

Our focus on non-cognitive abilities is motivated in part by the findings of the recent literature in economics and psychology regarding the significant role played by non-cognitive skills on schooling attainment, wages, and health outcomes (e.g., Heckman, Stixrud and Urzua 2006, Lindqvist and Vestmen 2011 and Taylor and Seeman 2000). In particular, self-efficacy has been identified by the majority of this work as being a positive predictor of successful outcomes along these dimensions. It is natural, therefore, to expect that it would also be important for household financial choices and outcomes.

People's capacity to believe that they can influence future outcomes through their actions has been captured by three related concepts in psychology: locus of control (Rotter 1966), the sense of mastery (Pearlin et al. 1981) and self-efficacy (Bandura 1986). High self-efficacy, mastery or having an internal locus of control have been shown to predict better physical and mental health (Taylor and Seeman 2000), better academic achievements (Kalil and Khalid 2010), higher job satisfaction and job performance (Judge and Bono 2001), and a less negative impact of encountering economic hardship or being in a low-income group on physical health and psychological well-being (Pudrovska et al. 2005, Lachman and Weaver 1998).

Here we document that self-efficacy also has beneficial effects in the context of household financial outcomes. We use data from the National Longitudinal Survey of Youth (NLSY) dataset. The measure regarding people's beliefs that their effort and actions can influence their future, the Pearlin mastery score, is obtained early in life. Participants are tracked and interviewed regularly, typically every two years. The NLSY provides a rich set of personal characteristics, labor market outcomes, and financial variables including indicators of delinquency, bankruptcy, and lack of access to credit.

To see how self-efficacy might relate empirically to financial outcomes, consider a situation where a person has to spend effort to avoid a poor financial outcome. For example, the person might need to find ways to reduce spending today in order to avoid defaulting on their credit card or mortgage payments in the future. A simple way to conceptualize this is as an effort choice problem, where providing effort is costly but it leads to an increase in the chance that the person will avoid a poor outcome later. People with lower self-efficacy scores have lower estimates for this increase than people with higher scores and thus choose to spend less effort, which will lead to a lower probability of avoiding a bad outcome. This implication captures our main empirical prediction: namely, that the frequency of occurrence of poor financial outcomes in the data will be be higher for people will low self-efficacy scores.

Our empirical analysis provides evidence consistent with this hypothesis. We find that lower self-efficacy scores during childhood predict a higher probability of future delinquency on debt payments. The effect of self-efficacy on delinquency is both substantial and robust; a one standard deviation increase in self-efficacy corresponds to a 15-20% decrease in the likelihood of delinquency, and this effect is not explained by differences in

gender, race, cognitive ability, educational attainment and income, contemporaneous or past. Further, we show that these differences in delinquency are not explained by differences in indebtedness. Finally, using variation in self-efficacy within sibling groups in the NLSY sample we confirm that delinquency rates decrease with self-efficacy. These results suggest that unobserved parental inputs, whether in childhood or adulthood, are not the driving force behind our main findings.

Our paper contributes to the emerging literature documenting the role of psychological factors on financial decisions. For example, moral beliefs are related to households' propensity to default on mortgages (Guiso et al. 2013). Recent work on education loans and investments highlights the role of self-control problems in borrowing decisions (Cadena and Keys 2013) and human capital investments (Cadena and Keys 2012). Furthermore, moderate optimism leads to working harder, investing more in stocks and having more savings (Puri and Robinson 2007), while feeling a lack of control over the future predicts a low interest in learning about investment options, being indebted over long horizons, and having low savings (Shapiro and Wu 2011, Caputo 2012, Cole et al. 2012).

2. Background on Self-efficacy

People's capacity to believe that they can influence future outcomes through their actions has been captured by three related concepts in psychology: locus of control (Rotter 1966), the sense of mastery (Pearlin et al. 1981) and self-efficacy (Bandura 1986). In our analysis, for reasons of data availability we focus on the Pearlin mastery measure.

2.1 Measuring Self-efficacy

The Pearlin Mastery score is compiled from responses to a battery of seven statements and is designed to measure "mastery," the extent to which individuals perceive themselves to be in control of their lives and future outcomes. For each statement, the respondent ranks the strength of their agreement on a scale of one ("strongly agree") to four ("strongly disagree"). The seven Pearlin statements are:

- (1) "No way I can solve some of the problems I have."
- (2) "Sometimes I feel that I am being pushed around in life."
- (3) "I have little control over the things that happen to me."
- (4) "I can do just about anything I really set my mind to."
- (5) "I often feel helpless in dealing with the problems of life."
- (6) "What happens to me in the future mostly depends on me."
- (7) "There is little I can do to change many of the important things in my life."

After reversing the scoring for the 4th and 6th items so that higher scores correspond to greater mastery, the 7 scores are summed to give a total score ranging between 7 and 28.

The Pearlin scores are then standardized and converted into percentiles, so vary between 0 and 100.

2.2 How might Self-efficacy Affect Likelihood of Default?

In this section, we sketch a simple model for understanding the role of self-efficacy in an individual's decision to default on outstanding debt. We highlight an effort choice problem describing a situation where a person has to spend effort to avoid a poor financial outcome, for instance, by identifying ways to cut spending today to avoid defaulting on their credit card or mortgage payments in the future. In this situation, increasing the effort e provided has some cost c(e) but it increases the probability that the person will obtain a high (H) rather than a low (L) outcome later. The actual probability of obtaining the high outcome *H* is the effort level *e*, and the probability of obtaining the low outcome *L* is (1-*e*). However, people believe that the probability of outcome *H* is e*m, where $m \in [0,1]$ measures their mastery, or self-efficacy. If m=1, people correctly assess that the probability of getting the high outcome is equal to the effort e they provide. If m<1, people have a pessimistic assessment of the impact their effort has on the probability of getting the high outcome. The person chooses the effort level e to maximize the perceived benefit minus the cost of effort, i.e., they maximize the expression $\{-c(e) + \beta [emH + (1-em)L]\}$, where β captures the person's patience. Assuming the cost function is $c(e) = \gamma e^2/2$, the first order condition implies that the effort level selected is $e^* = \beta m(H-L)/\gamma$. Hence the probability that the low outcome L is realized will be 1 for the lowest mastery (i.e., m=0) people and will be 1- $\beta(H-L)/\gamma$ for the highest mastery ones (i.e., m=1). Therefore, we have a simple expression for how differences in the mastery level should relate to differences in the observed frequency of low outcomes, such as delinquency or bankruptcy events in our data. Namely, $Pr\{L \text{ outcome if } m=0\} - Pr\{L \text{ outcome if } m=1\} = \beta(H-L)/\gamma$. Equivalently, this can be expressed as: $dPr\{L \ outcome\}/dm = -\beta(H-L)/\gamma$.

This simple example provides the intuition for our main empirical prediction: we expect the likelihood of delinquency to decline with mastery. Moreover, the example yields a cross-sectional prediction that we will examine in future tests: namely, the effect of mastery on the likelihood of poor financial outcomes should be stronger in subsamples of individuals characterized by more patience β , lower cost of effort γ , or those facing an action with larger stakes H-L.

3. Data and Summary Statistics

3.1 Data

Our primary data source is the National Longitudinal Survey Youth 1979, Child and Young Adult sample (NLSY79CYA), a longitudinal survey that follows the children of women in the original NLSY 1979 sample throughout childhood and into adulthood. The NLSY79CYA survey, which is administered every two years, began in 1986 and continues today, with data released through the 2010 interview.

The survey questionnaire has two components, a child questionnaire administered to those age 14 or younger and a young adult questionnaire administered to those age 15 and older. The child survey focuses on the family and schooling environments, and the child's health as well as his cognitive, emotional and social development, while the young adult survey continues to focus on schooling, psychological development and social development, but also tracks respondents' marital history, employment history and financial history as they move into adulthood. Despite the label "young adult", the latter

questionnaire is used for sample members throughout adulthood, which means that by 2010, we observe a number of sample members that are well into their 30s.

The original NLSY79 survey followed roughly 13,000 individuals, and by 2010 the Child and Young sample on which we focus includes 11,500 individuals. In our analysis of credit delinquency and self-efficacy, we focus on adults that are 21 years or older as of 2010, at which point they are more likely to be financially independent from their parents. This portion of the sample includes 3,699 individuals. Below we describe the key variables for our analysis and discuss the summary statistics, which are reported in Table 1.

3.2 Summary Statistics for Regression Sample

First, let us describe the measures of non-cognitive and cognitive abilities. Among non-cognitive traits we focus on the Pearlin Mastery score, a measure of self-efficacy. The Pearlin score is taken in each young adult interview, but we focus on the earliest measure, taken between the ages of 15 and 18. The Pearlin score is normalized and measured in percentiles relative to the distribution of raw scores within the sample at the time the measure was taken. The average Pearlin score in our sample is 48.6, and the standard deviation is 28.3.

As an assessment of cognitive ability, the survey includes the Peabody Individual Achievement Test (PIAT), which tests math ability as well as reading recognition and reading comprehension. These measures of cognitive ability are taken throughout childhood, and we focus on the last available measure, which most commonly is taken at age 13 or 14. The PIAT ability scores are also measured in percentiles, normalized by age

group relative to scores in a national sample in 1968. Within our sample the averages for math, reading recognition and reading comprehension are 46.3, 52.7 and 41.4, respectively, and the standard deviation for each measure is roughly 30.

Turning to education, 15 percent of sample members have a college degree, 33 percent have completed some college, 35% have only a high school diploma and 17% have failed to complete high school. The rate of college degree completion is lower than U.S. averages, likely because many sample members are still in their early 20s. The median respondent is 25 years of age, with each two-year age bin between 21 and 29 encompassing roughly 20% of the sample, and those age 29 years and more representing 18% of the sample.

Racially, the composition of the sample is tilted toward minorities, with both blacks (36 percent of the sample) and Hispanics (22 percent of the sample) being intentionally oversampled in the original NLSY sample. Finally, the average household includes just over three people and 22% of sample members are married.

Next, we discuss the key economic and financial measures in our analysis. Income is measured in each wave of the survey, throughout adulthood. Average household income in 2010 is just under \$28,000 per year, while average income during adulthood is \$13,400 per year.

Among household financial variables, the data on household debt are quite rich, while the data on assets are less comprehensive and detailed. Since 2000, each respondent to the young adult questionnaire reports the outstanding balances on credit card, vehicle and mortgage loans, as well as the estimated value of the underlying collateral for the latter

two categories. In 2010, various questions about credit delinquency were added to the survey. These measures comprise the key dependent variables in our study.

On the asset side, the survey measures real asset holdings via home and vehicle ownership, but it lacks information on financial asset holdings. Within our sample, 17% of sample members own a home and 66% own a vehicle.

As of 2010, the average total debt balance across all sample members is \$21,800. 38% of sample members are credit card holders, with an average debt balance of \$2,500 among cardholders. 31% of sample members have vehicle debt outstanding, with an average debt balance of \$11,600 among vehicle debtors.

With regard to credit delinquency, the data indicate that 11.7% of households with credit cards and 8.3% of households with vehicle loans have been at least 60 days behind on payments over the last year. The mortgage delinquency measure differs slightly in that it measures delinquency over the 2 years rather than the prior 12 months. 8.9% of individuals that owned a home at some point during that 2-year period report being delinquent at some point over those 2 years. Meanwhile, 20.9% of respondents report having had an account sent to a bill collector in the last 12 months and 1% report having filed for bankruptcy during the last 12 months.

4. How Does Credit Delinquency Vary with Self-efficacy?

In the empirical analysis that follows, we test for differences in credit delinquency predicted by self-efficacy, using the following linear probability model:

The subscript i in this equation indexes individuals. The dependent variable, Delinquency, is an indicator for credit delinquency or default over the prior 12 months. We examine in separate models each of the five measures of delinquency discussed above. The key independent variable, Self-efficacy, is the Pearlin Score expressed as a percentile. The coefficient of interest is β , which measures how the likelihood of delinquency varies with self-efficacy. The vector X contains individual-level control variables, which we discuss below.

The approach to identifying the effect of self-efficacy on delinquency is to use all the observed variation in self-efficacy and to condition on other observed differences, e.g. in cognitive ability, education and income, that may correlate with both self-efficacy and delinquency. Given that we are not isolating exogenous variation in self-efficacy through a natural experiment, these control variables play a very important role. While this approach has limitations, the NLSY data are quite rich, so we are in a good position to observe and control for important differences between those with high and low self-efficacy.

Most importantly, we control for differences in cognitive ability, educational attainment and income. Naturally, income is a strong predictor of delinquency, and both cognitive ability and educational attainment are important predictors of both current and future economic success. Furthermore, cognitive ability and knowledge, particularly financial knowledge, are known to affect the likelihood of financial mistakes and may thereby influence delinquency. As controls for cognitive ability and education, we include each of the three PIAT ability measures and the set of four dummy variables that measure

educational attainment. Next, we control for income, including both contemporaneous and past income through the following two measures: log of family income (prior 12 months) and log of average family income (during adulthood). We also include dummies for home ownership and vehicle ownership as proxies for real asset holdings. Given that credit delinquency takes some time to develop, we control for stage of lifecycle with indicators for age range (6 categories total, with 2-year bins between 21 and 30, and a single bin for individuals over 30 years of age). We control for household size, which can affect the both the level and variability in expenditures, and marital status, which can proxy for intrahousehold insurance. Lastly, we control for race, gender and marital status.

4.1. Examining the correlates of self-efficacy in the regression sample

As a first step in the empirical analysis, we examine the correlation between self-efficacy and the control variables in our regression sample. We start with univariate OLS regressions of self-efficacy on individual characteristics and then run a multivariate OLS regression of self-efficacy on the full set of individual characteristics. The estimation results are displayed in Table 2. As shown in the first three columns, each measure of cognitive ability is positively correlated with the Pearlin score, meaning that individuals with greater ability have greater self-efficacy. This relationship remains in the pooled regression with all covariates, as math ability and reading recognition in particular display a positive correlation with the Pearlin score. Education correlates very strongly with self-efficacy, in part because educational attainment proxies for ability. Even controlling for ability and other covariates, however, educational attainment co-varies strongly with self-efficacy.

This pattern fits with evidence from (Coleman and DeLeire 2003; Kalil and Khalid 2010) that individuals with higher self-efficacy choose to invest more effort in building human capital. Income and asset ownership also increase with self-efficacy, but only in the univariate models; with the full set of covariates, there is little relationship between the Pearlin score and income or asset ownership. Race shows little relationship with self-efficacy when excluding other covariates, but displays a notable pattern in the pooled model: interestingly, self-efficacy is lower among whites than among Hispanics (a 2.1 percentile point difference) and African-Americans (a 4.9 percentile point difference). Gender and age do not correlate strongly with self-efficacy. Finally, consistent with evidence that women with low self-efficacy are more likely to bear children out of wedlock, we find that respondents with lower Pearlin scores live in larger households, on average, despite the fact that marital status is unrelated to self-efficacy.

4.2. Results on credit delinquency and self-efficacy

Regression results for credit delinquency are displayed in Table 3. The first of these tables shows regression results for models with 60-plus day delinquency as the dependent variable. We consider each loan category separately and restrict the sample to the group at risk of delinquency. For credit card loans we restrict the sample to individuals who report having a credit card, and for vehicle loans we restrict the sample to individuals who report having vehicle debt outstanding. For mortgage loans, we restrict the sample to individuals that reported owning a home over the prior two years (the same question is not asked regarding mortgage debt over the prior two years).

Starting with credit cards, we observe lower rates of delinquency among those with greater self-efficacy. In the first specification, which lacks control variables, the coefficient on the Pearlin score is -0.072 (p < 0.05). This estimate implies that the likelihood of delinquency decreases by 7.2 basis points for every percentile point increase in the Pearlin score. Controlling for cognitive ability and educational attainment reduces the coefficient on self-efficacy modestly to -0.063, but this estimate remains significant at the 5% level. Finally, inclusive of the full set of control variables, the coefficient on the Pearlin score is -0.068 (p < 0.05). Extrapolating from this estimate, the differences in delinquency predicted by self-efficacy are economically meaningful: a one standard deviation increase in the Pearlin score (28 percentile points) corresponds to a 2 percentage point reduction in the delinquency rate, a sizeable difference relative to the sample average for credit card delinquency (11.7%).

Moving on to vehicle loans, we again find that the likelihood of delinquency declines with self-efficacy. In the univariate model, we estimate a coefficient of -0.074 (p < 0.05) on the Pearlin score. Adding the full set of controls reduces that coefficient to -0.056, but the estimate remains significant at the 10% level. In proportional terms, the implied difference in delinquency rate is quite similar to what we find for credit cards. A one standard deviation increase in self-efficacy corresponds to a 1.6 percentage point reduction, roughly a 20% decline compared to the average delinquency rate of 8.3%.

Finally, the last three columns of Table 3 show estimation results for mortgage delinquency. Again we find negative point estimates on the self-efficacy measure, but of substantially smaller magnitude than for credit card and vehicle loans, and without statistical significance. The estimates in the mortgage specification also less precise due to

a smaller sample size (roughly $\frac{1}{2}$ the size of the sample for the other two loan categories). In the specification with the full set of controls, the coefficient estimate for the Pearlin score is -0.026.

In the sections that follow, we investigate the reasons for the negative correlation between delinquency and perceived self-efficacy.

4.3. Do Debt Balances Vary with Self-efficacy?

We begin by testing whether debt balances themselves are higher among those with lower self-efficacy. In that case, individuals with low self-efficacy may default more often because they face a greater debt service burden and accordingly are unable to weather shocks to income or consumption. In addition, they may default more often because of moral hazard – the gain from defaulting is larger for those that are more deeply indebted.

As noted above, the NLSY measures debt balances for each loan category, so we can test this hypothesis directly. For the dependent variable, we measure indebtedness with the debt-to-income ratio, and take a log transformation (log of (1 + debt-to-income)) to adjust for right skew in debt-to-income. We use the same controls as in the prior analysis of delinquency. Table 4 shows the results from this analysis. We find that total indebtedness, summing over credit card, vehicle and mortgage loans, decreases with self-efficacy. The coefficient on Self-efficacy is -0.0004 (p < 0.05), which implies a 1 percentile increase in self-efficacy reduces the log debt-to-income ratio by roughly 4 basis points. The effect is quite modest: extrapolating from the point estimate, a one standard deviation increase in self-efficacy corresponds to a 1.1% reduction in the total debt-to-income ratio. This pattern

in total debt-to-income is driven entirely by mortgage debt. For both credit card and vehicle loans, we find no relationship between log debt-to-income and self-efficacy. Meanwhile for mortgage loans the results look very similar to the total debt results: the coefficient on self-efficacy is -0.0004 (p < 0.05).

Next, we return to the analysis of delinquency and test whether these differences in loan balances, though they are limited to mortgage loans, account for the main findings on delinquency and self-efficacy. We do so by including the log debt-to-income ratio for each loan category as a control in the delinquency regressions. Estimation results, which are shown in Table 5, indicate that differences in debt balances are not driving the main findings. For both credit card and vehicle loans, the coefficients on self-efficacy are very close to the main findings.

Overall, we find that mortgage indebtedness declines with self-efficacy, but that controlling for indebtedness has no impact on the estimated relationship between self-efficacy and delinquency. These results suggest that self-efficacy does not influence credit card and vehicle loan delinquency through its effect on loan balances.

4.4. Do Parental Inputs Explain the Role of Self-efficacy in Predicting Default?

In the next portion of the analysis, we examine whether our main findings are driven by some parental or environmental input that is shared among siblings. Prior work has shown that self-efficacy and the related mastery and locus of control beliefs are influenced by people's circumstances. In particular, individuals with higher socio-economic status (Gecas 1989), and those with more educated and more nurturing parents (Whitbeck

et al. 1997, Lewis et al. 1999) have better scores on these measures. It is also natural to believe that a person's upbringing also influences his propensity to default on debt later in life, whether due to parental inputs during childhood – shaping moral attitudes, for example – or due to parental inputs during adulthood, such as financial support during a period of economic hardship.

A powerful feature of the NLSY79CYA survey is that it follows sibling groups and includes identifiers that link siblings to each other and to the original NLSY79 mother. A substantial portion of the sample is composed of children with siblings that are also present in the sample: among the 3,699 individuals in our regression sample, 1,179 are lone children, while 1,610 are part of a sibling pair, and the remaining 910 are part of a sibling group of three or more. This feature of the data allows us to study differences in self-efficacy and delinquency within sibling groups, through models that include siblinggroup fixed effects. These fixed effects serve as controls for unobserved genetic inheritance that is correlated among siblings, as well as parental support in childhood and adulthood that is common among siblings.

Table 6 shows estimation results for this analysis. Aside from the inclusion of sibling-group fixed effects, these models are identical to the main specification. Beginning with credit card delinquency, we estimate a coefficient of -0.151 (p < 0.05) on the Pearlin score in a baseline specification with sibling FEs but without other control variables. Adding the control variables increases the coefficient slightly to -0.165 (p < 0.01). Similarly, for vehicle loans we find that delinquency decreases with self-efficacy, by 11.7 basis points (p < 0.10) for every 1 percentile point increase in the Pearlin Mastery score in a model with the full set of controls. For mortgage delinquency, coefficient on self-efficacy has a negative

point estimate, but again is quite imprecisely estimated and varies substantially when control variables are added to the model.

Qualitatively, the variation in delinquency and default within sibling groups follows the same pattern as in the main analysis: individuals with higher self-efficacy are less likely to experience credit delinquency and default. Quantitatively, the results differ: the sibling fixed effects estimates imply larger effects of Pearlin score on credit delinquency, with coefficients that are roughly twice the size of those in the main specifications.

5. Discussion

Our analysis provides suggestive, if not conclusive, evidence that self-efficacy is an important determinant of household default decisions.

It is important to emphasize that our findings are not subject to a concern about reverse causality. If self-efficacy and delinquency were measured contemporaneously, one might worry that respondents are expressing lower mastery or less control over their lives because they have recently defaulted on debt. For this reason we take advantage of the longitudinal structure of the NLSY and use a self-efficacy measure from late childhood or early adulthood, not only before the delinquency measure is taken but before the respondent has established much independent financial history whatsoever. As a result, the negative correlation that we document does not represent the effect of past financial default on self-efficacy.

In light of evidence that self-efficacy and other non-cognitive traits have important effects on economic outcomes, omitted variables bias is certainly possible. We control for a

number of important observable differences such as income history and educational attainment, but there are nevertheless unobserved variables such as financial wealth and expectations for income growth and uncertainty that may also explain default. A related concern is that our control variables suffer from measurement error, and that self-efficacy proxies for unmeasured ability, for example. Finally, it is possible that spending patterns differ among those with low self-efficacy; though we control for income and household size, it may be that individuals with low self-efficacy face more frequent expense shocks, for example due to health problems. In future versions of the analysis, we hope to test and rule out these alternatives, where possible.

6. Conclusion

Recent work in economics and psychology has emphasized the importance of non-cognitive abilities in educational and job market success. Here, we find that non-cognitive traits also play an important role in determining financial success. More specifically, we find that measures of self-efficacy predict substantial differences in credit delinquency later in life.

Identifying the role of non-cognitive abilities such as self-efficacy on household financial outcomes is useful because, unlike other characteristics that may be predetermined, non-cognitive skills can be improved via interventions at various stages in life. For example, Heckman, Pinto and Savelyev (2013) show that an intervention in early childhood, the Perry Preschool program, improved participants' schooling and labor market outcomes mainly through an increase in non-cognitive skills. It is therefore possible

that by helping people believe more in their own capacity to influence the future, they will in fact take action and achieve better financial outcomes. We believe this is a fruitful avenue for future work in household finance.

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Table 1: Summary Statistics

	Mean	Median	Standard Deviation	N
Non-cognitive Ability, Age 15-18				
Self-efficacy (pctile)	48.6	55.7	28.3	3,699
Cognitive Ability, Age 13-15				
Math (pctile)	46.3	44.0	27.4	3,624
Reading Recognition (pctile)	52.7	55.0	30.3	3,624
Reading Comprehension (pctile)	41.4	38.0	27.0	3,584
Education as of 2010				
Less than HS diploma	0.17	0	0.38	3,699
HS diploma	0.35	0	0.48	3,699
Some college	0.33	0	0.47	3,699
College degree	0.15	0	0.36	3,699
Demographics as of 2010, where applicable				
Age	25.6	25	3.2	3,699
Age, 21-22 (indicator)	0.20	0	0.40	3,699
Age, 23-24	0.21	0	0.41	3,699
Age, 25-26	0.21	0	0.41	3,699
Age, 27-28	0.20	0	0.40	3,699
Age, 29-30	0.11	0	0.31	3,699
Age, 30+	0.07	0	0.25	3,699
Hispanic	0.22	0	0.42	3,699
African American	0.36	0	0.48	3,699
White	0.42	0	0.49	3,699
Female	0.52	1	0.50	3,699
Number HH members	3.27	3	1.61	3,699
Married	0.22	0	0.41	3,699
Income and Assets				
HH income, 2010 (\$ thousands)	27.9	18.5	30.8	3,699
HH income, mean in adulthood (\$ thousands)	13.4	10.0	12.6	3,699
Homeowner, 2010	0.17	0	0.37	3,692
Vehicle owner, 2010	0.66	1	0.47	3,687
Household Debt as of 2010				
Credit card holder?	0.38	0	0.49	3,689
Vehicle loan outstanding?	0.31	0	0.46	3,651
Total household debt (\$ thousands)	21.8	0	6.1	3,699
Total household debt-to-income ratio (if debt > 0)	0.87	0.36	1.03	1,676
Credit card loan balance for cardholders (\$ thousands)	2.5	0.8	4.9	1,373
Vehicle loan balance for vehicle debtors (\$ thousands)	11.6	10	9.6	1,146
Mortgage loan balance for mortgagors (\$ thousands)	120.0	108	75.6	471
Credit Delinquency over Prior 12 months, 2010				
Credit card late 60+ days (% of credit card holders)	11.7	0	32.2	1,383
Vehicle loan late 60+ days (% of vehicle debtors)	8.3	0	27.6	1,134
Mortgage loan late 60+ days, prior 2 years (% homeowners	8.9	0	28.5	695

=					penaent v	uriubici be	ir ciricacy	(pctile), Me						
Math (pctile)	0.128***													0.056**
	(0.02)	0.120***												(0.02)
Reading Recog (pctile)		0.139***												0.093**
		(0.02)	0.117***											(0.02) 0.01
leading Comp (pctile)			(0.02)											(0.03)
IS diploma			(0.02)	4.873***										2.342*
is dipionia				(1.36)										(1.42)
ome college				8.013***										3.713*
ome conege				(1.37)										(1.52)
ollege degree				11.958***										5.055**
onege degree				(1.62)										(1.89)
og (HH income 2010)				(1.02)	1.448***									0.392
-8 ((0.33)									(0.57)
og (mean income as a	dult)				()	2.076***								-0.041
	,					(0.50)								(0.96)
lomeowner							2.745**							1.123
							(1.25)							(1.43)
Vehicle owner								2.686***						0.738
								(0.98)						(1.14)
African American									1.868					2.834*
									(1.25)					(1.30)
/hite									0.902					-2.163*
									(1.22)					(1.28)
emale										-0.074				-0.642
										(0.93)				(0.96)
ge 21-22											-3.499*			-3.681
											(2.08)			(2.30)
ge 23-24											-1.881			-2.092
											(2.07)			(2.20)
ge 25-26											-1.014			-1.215
											(2.07)			(2.14)
ge 27-28											-3.972*			-4.507*
											(2.08)			(2.10)
ge 29-30											-0.653			-0.97
											(2.29)	4 4 0 5 4 4 4		(2.30)
lumber HH members												-1.127***		-0.560*
Anumin d												(0.29)	1 275	(0.31)
Married													1.375	-0.015
													(1.13)	(1.33)
Observations	3,624	3,624	3,584	3,699	3,699	3,699	3,692	3,687	3,699	3,699	3,699	3,699	3,699	3,576
R-squared	0.016	0.022	0.013	0.017	0.005	0.005	0.001	0.002	0.001	0.000	0.002	0.004	0.000	0.037

delta and the angle of the angl

*** p<0.01, ** p<0.05, * p<0.10

Table 3: Loan Delinquency and Self-efficacy

Part	Table 3. Loan Dennque	Dependent variable: Indicator for 60+ day delinquency										
Self-efficacy (pctile) (1) (2) (3) (4) (5) (6) (7) (8) (9) Self-efficacy (pctile) -0.062*** -0.063*** -0.068*** -0.074*** -0.055** -0.055** -0.009*** -0.030** (0.030) -0.030*** (0.030) -0.030*** (0.030) -0.030*** (0.030) -0.030*** (0.030) -0.030*** (0.030) 0.030*** (0.030) 0.030*** (0.030) 0.030*** (0.030) 0.030*** (0.030) 0.030*** (0.030) 0.030*** (0.030) 0.030*** (0.030) 0.030*** (0.030) 0.022*** (0.055) 0.000*** (0.050) 0.091*** (0.050) 0.003*** (0.050) 0.091*** (0.050) 0.091*** (0.050) 0.003*** (0.050) 0.091*** (0.050) 0.003*** (0.050) 0.003*** (0.050) 0.005** (0.050)		Cre	edit Card L	=	ic variable.		=	-				
Math (pctile)					(4)							
Math (pctile)	Self-efficacy (pctile)	-0.072**	-0.063**	-0.068**	-0.074**	-0.055*	-0.056*	-0.021	-0.013	-0.026		
Math (pctile) .0.074* 0.028 .0.065 .0.009 0.090 0.122** Reading Recog (pctile) 0.010** 0.099** .0.036 .0.039 0.003* 0.007* Reading Comp (pctile) 0.049* 0.015 0.074* 0.095** 0.167*** -0.142** 0.014* 0.049 0.015 0.074* 0.095** 0.167*** -0.142** 0.014** 0.049 0.015 0.074* 0.095** 0.167*** -0.142** 0.014** 0.049 0.015 0.074* 0.095** 0.167*** -0.142** 0.053 0.053 0.053 0.053 0.052 0.053 0.053 0.052 0.053 0.053 0.052 0.053 0.053 0.052 0.053 0.053 0.052 0.053 0.052 0.053 0.053 0.052 0.052 0.053 0.052 0.053 0.052 0.052 0.052 0.052 0.052 0.052 0.052 0.052 0.052 0.052 0.052 0.052 0.052 0.052 0.	, , , , , , , , , , , , , , , , , , ,											
Reading Recog (pctile)	Math (pctile)			-								
Reading Comp (pctile)			(0.041)	(0.042)		(0.040)	(0.042)		(0.055)	(0.057)		
Reading Comp (pctile) -0.049 -0.015 0.074* 0.095** -0.167*** 0.142** 0.042* 0.042* 0.042* 0.042* 0.043* 0.058*	Reading Recog (pctile)		0.107**	0.099**		-0.036	-0.039		0.093*	0.091*		
MS diploma 1,0044 1,0044 1,0042 1,0042 1,0042 1,0045 1,0058 1,058 1,0058 1,0058 1,0058 1,0058 1,0058 1,0058 1,0058 1,0058 1,0058 1,0058 1,0058 1,0058 1,0058 1,0058			(0.042)	(0.042)		(0.039)	(0.039)		(0.052)	(0.053)		
HS diploma 3.238 3.267 -1.995 2.660 -1.816 2.2182 4.0387 (3.042) 3.0650 (4.009) (4.038) 4.0494 4.0384 4.0494 4.0384 4.0494 4.0384 4.0419 3.0350 (3.082) (4.141) (4.243) 4.0414 4.0424	Reading Comp (pctile)		-0.049	-0.015		0.074*	0.095**		-0.167***	-0.142**		
Some college (3.876) (3.883) (3.042) (3.065) (4.009) (4.038) College degree -2.182 -3.173 -6.459** -6.723** -4.711 4.914 College degree 5.721 -6.894* -9.309*** -9.125** -7.485* -6.528 Log (HH income 2010) -2.956** -1.993 (4.544) (4.722) Log (mean income as alult) 1.080 -3.94** -0.339 -7.465** -7.99** Homeowner 3.954* -2.224 -2.233 -7.909*** -7.909*** Vehicle owner -3.954* -2.240 -2.150 -2.166* -2.717 (4.032) African American 8.19**** -1.559 -2.150 -2.165 -2.171 -2.717 (4.032) -4.179 -4.			(0.044)	(0.044)		(0.042)	(0.042)		(0.058)	(0.058)		
Some college -2.182 -3.173 -6.459** -6.723** -4.711 -4.914 College degree -5.721 6.894* -9.309*** -9.125** -6.528 -6.528 Log (HH income 2010) -2.956** -1.993 -1.993 -5.754*** -5.754*** Log (mean income as adult) 1.080 -1.993 -1.993 -5.754*** -5.754*** Log (mean income as adult) 1.080 -0.339 -0.339 -7.909*** Homeowner -3.954* -2.224 -2.233 -2.233 -2.559 Homeowner -1.559 -1.559 -1.655 -1.657 -2.717 African American -1.559 -1.655 -1.655 -4.179 -4.179 White -1.559 -1.655 -1.654 -2.201 -2.201 -2.201 -2.202 -2.202 -2.202 -2.202 -2.202 -2.202 -2.202 -2.202 -2.202 -2.202 -2.202 -2.202 -2.202 -2.202 -2.202 -2.202 -2.202 -2.202	HS diploma		3.238	3.267		-1.995	-2.660		-1.816	-2.213		
College degree			(3.876)	(3.853)					(4.009)	(4.038)		
College degree -5.721 -6.894* -9.309*** -9.125** -7.485* 6.528 Log (HH income 2010) 2.956** (1.306) -9.309*** -9.125** (4.544) (4.722) Log (mean income as adult) 1.080 -0.339 -0.339 7.909*** Log (mean income as adult) 2.224 -0.339 -0.339 7.909*** Homeowner 2.355** -0.354* -0.339 -0.579** 7.909*** Vehicle owner 2.355** -1.559 -2.1559 -2.156 2.157 -2.171 (4.032) African American 8.197*** -1.559 <t< td=""><td>Some college</td><td></td><td>-2.182</td><td></td><td></td><td>-6.459**</td><td>-6.723**</td><td></td><td>-4.711</td><td>-4.914</td></t<>	Some college		-2.182			-6.459**	-6.723**		-4.711	-4.914		
Log (HH income 2010)						-						
Continue Continue	College degree											
Continue Continue			(3.986)	-		(3.449)			(4.544)			
	Log (HH income 2010)											
Moneowner										. ,		
Homeowner	Log (mean income as ac	dult)										
Vehicle owner (2.288) (2.116) (2.717) African American 8.197*** 1.655 4.179 White (2.642) (2.437) 3.480) White (2.214) (2.196) 2.290) Female 4.333** 1.547 2.262) age 21-22 8.067* 1.2542*** 3.688 age 21-22 8.067* 1.2542*** 3.688 age 23-24 3.751 1.1573**** 3.688 age 25-26 5.048 9.010*** 6.414 age 27-28 4.174 5.548 9.010*** 6.414 age 29-30 4.174 5.258 5.258 5.416 Mumber HH members 0.360 0.955 1.305 Married 2.690 0.234 0.0608 0.921 Observations 1,383 1,351 1,314 1,109 1,109 695 681 679				. ,						(2.529)		
Vehicle owner -1.559 2.717 (2.470) (2.470) (4.032) African American 8.197**** 1.655 -4.179 (2.642) (2.437) (3.480) White -1.503 -2.505 -5.629* (2.214) (2.196) (2.920) Female 4.333** 1.547 0.777 1.762 -8.667* 12.542*** -3.688 age 21-22 -8.067* -12.542**** -3.688 age 23-24 -3.751 -11.573*** -7.530 age 25-26 -5.048 -9.010*** -6.414 age 27-28 -4.174 -5.258 -5.416 age 29-30 -2.491 -8.368** -5.416 (4.369) -3.538) (3.631) (3.941) Number HH members 0.360 0.955 1.305 (0.637) (0.608) -0.234 -2.262 (0.637) (2.210) (2.019) 695 681 679	Homeowner											
African American	** 1 - 1						(2.116)			0.545		
African American 8.197***	Vehicle owner											
White (2.642) (2.437) (3.480) Female (2.214) (2.196) (2.920) Female 4.333** 1.547 0.777 age 21-22 8.067* -12.542*** -3.688 4.4755) (4.755) (4.211) (6.117) age 23-24 -3.751 -11.573**** -7.530 age 25-26 5.048 -9.010*** -6.414 age 27-28 -4.174 5.258 -5.416 age 29-30 -2.491 8.368** -8.368** -4.198 Aumer HH members 0.360 0.955 1.305 Married -2.690 -2.690 -0.234 -2.262 Observations 1,383 1,351 1,134 1,109 1,109 695 681 679	A fui ann Amanian						1 (55					
White -1.503 -2.505 -5.629* Female (2.214) (2.196) (2.920) Female 4.333** 1.547 0.777 (1.762) (1.684) (2.262) age 21-22 -8.067* -12.542**** -3.688 (4.755) (4.211) (6.117) age 23-24 -3.751 -11.573**** -7.530 age 25-26 5.048 -9.010*** -6.414 (4.130) (3.666) (4.026) age 27-28 4.174 -5.258 -5.416 (4.016) (3.538) (3.631) age 29-30 -2.491 -8.368** -4.198 (4.369) (3.803) (3.941) Number HH members 0.360 0.955 1.305 (0.637) (0.608) (0.921) Married -2.690 -0.234 -2.262 (5.555) 681 679	Afficali Afficilicali											
Female 4.333** 1.547 0.777 age 21-22 -8.067* -12.542*** -3.688 age 23-24 -3.751 -11.573*** -7.530 age 25-26 -5.048 -9.010*** -6.414 age 27-28 4.174 -5.258 -5.416 age 29-30 -2.491 8.368** -4.198 Number HH members 0.360 0.955 1.305 Married -2.690 0.6637 (0.608) (0.921) Observations 1,383 1,351 1,351 1,134 1,109 1,109 695 681 679	White			-			-					
Female 4.333** 1.547 0.777 age 21-22 -8.067* -12.542*** -3.688 (4.755) (4.211) (6.117) age 23-24 -3.751 -11.573*** -7.530 age 25-26 -5.048 -9.010** -6.414 age 27-28 -4.174 -5.258 -5.416 age 29-30 -2.491 -8.368** -4.198 (4.369) (3.803) (3.941) Number HH members 0.360 0.955 1.305 Married -2.690 -0.234 -2.262 (2.210) (2.210) 1,134 1,109 1,109 695 681 679	winte											
age 21-22 (1.762) (1.684) (2.262) age 21-22 -8.067* -12.542**** -3.688 (4.755) (4.211) (6.117) age 23-24 -3.751 -11.573**** -7.530 age 25-26 -5.048 -9.010** -6.414 age 27-28 -4.174 -5.258 -5.416 age 29-30 -2.491 -8.368** -4.198 Number HH members 0.360 0.955 1.305 Married -2.690 0.955 1.305 Married -2.690 -0.234 -2.262 (2.210) (2.210) (2.019) 695 681 679	Female			-								
age 21-22 -8.067* -12.542*** -3.688 (4.755) (4.211) (6.117) age 23-24 -3.751 -11.573*** -7.530 age 25-26 -5.048 -9.010** -6.414 age 27-28 -4.174 -5.258 -5.416 (4.016) (3.538) (3.631) age 29-30 -2.491 -8.368** -4.198 (4.369) (3.803) (3.941) Number HH members 0.360 0.955 1.305 (0.637) (0.608) (0.921) Married -2.690 -0.234 -2.262 (2.210) (2.210) (2.019) 695 681 679	Temate											
age 23-24 -3.751 -11.573**** -7.530 age 25-26 -5.048 -9.010** -6.414 age 27-28 -4.174 -5.258 -5.416 age 29-30 -2.491 -8.368** -4.198 Number HH members 0.360 0.955 1.305 Married -2.690 -0.234 -2.262 (2.210) (2.210) 1,134 1,109 1,109 695 681 679	age 21-22											
age 23-24 -3.751 -11.573*** -7.530 age 25-26 -5.048 -9.010** -6.414 age 27-28 -4.174 -5.258 -5.416 (4.016) (3.538) (3.631) age 29-30 -2.491 -8.368** -4.198 Number HH members 0.360 0.955 1.305 Married -2.690 -0.234 -2.262 (2.210) (2.210) 1,134 1,109 1,109 695 681 679	480 = 1 = -											
age 25-26 -5.048 -9.010** -6.414 age 27-28 -4.174 -5.258 -5.416 age 29-30 -2.491 -8.368** -4.198 Number HH members 0.360 0.955 1.305 Married -2.690 -0.234 -2.262 (2.210) (2.210) 1,134 1,109 1,109 695 681 679	age 23-24											
age 25-26 -5.048 -9.010** -6.414 (4.130) (3.666) (4.026) age 27-28 -4.174 -5.258 -5.416 (4.016) (3.538) (3.631) age 29-30 -2.491 -8.368** -4.198 (4.369) (3.803) (3.941) Number HH members 0.360 0.955 1.305 (0.637) (0.608) (0.921) Married -2.690 -0.234 -2.262 (2.210) (2.019) (2.555) Observations 1,383 1,351 1,351 1,134 1,109 1,109 695 681 679	O											
age 27-28 (4.130) (3.666) (4.026) age 27-28 -4.174 -5.258 -5.416 (4.016) (3.538) (3.631) age 29-30 -2.491 -8.368** -4.198 (4.369) (3.803) (3.941) Number HH members 0.360 0.955 1.305 (0.637) (0.608) (0.921) Married -2.690 -0.234 -2.262 (2.210) (2.210) (2.019) (2.555) Observations 1,383 1,351 1,351 1,134 1,109 1,109 695 681 679	age 25-26											
age 29-30 -2.491 -8.368** -4.198 Number HH members 0.360 0.955 1.305 Married -2.690 -0.234 -2.262 (2.210) (2.210) 1,134 1,109 1,109 695 681 679	_			(4.130)			(3.666)			(4.026)		
age 29-30 -2.491 -8.368** -4.198 Number HH members 0.360 0.955 1.305 Married -2.690 -0.234 -2.262 (2.210) (2.210) (2.019) 695 681 679	age 27-28			-4.174			-5.258			-5.416		
Number HH members (4.369) (3.803) (3.941) Number HH members 0.360 0.955 1.305 (0.637) (0.608) (0.921) Married -2.690 -0.234 -2.262 (2.210) (2.019) (2.555) Observations 1,383 1,351 1,351 1,134 1,109 1,109 695 681 679				(4.016)			(3.538)			(3.631)		
Number HH members 0.360 (0.637) 0.955 (0.608) 1.305 (0.921) Married -2.690 (2.210) -0.234 (2.019) -2.262 (2.555) Observations 1,383 1,351 1,351 1,134 1,109 1,109 695 681 679	age 29-30			-2.491			-8.368**			-4.198		
Married (0.637) (0.608) (0.921) -2.690 (2.210) (2.019) (2.555) Observations 1,383 1,351 1,351 1,134 1,109 1,109 695 681 679				(4.369)			(3.803)			(3.941)		
Married -2.690 (2.210) -0.234 -2.262 (2.555) Observations 1,383 1,351 1,351 1,134 1,109 1,109 695 681 679	Number HH members			0.360			0.955			1.305		
Observations 1,383 1,351 1,351 1,134 1,109 1,109 695 681 679				(0.637)			(0.608)			(0.921)		
Observations 1,383 1,351 1,351 1,134 1,109 1,109 695 681 679	Married			-2.690			-0.234			-2.262		
				(2.210)			(2.019)			(2.555)		
	Observations	1,383	1,351	1,351	1,134	1,109	1,109	695	681	679		
·	R-squared	0.004	0.022	0.064	0.006	0.025	0.054	0.000	0.020	0.074		

Notes: This table shows OLS estimation results for regressions of an indicator for 60+ day delinquency (by debt category) on self-efficacy and control variables. Among the covariates that are categorical variables, the exluded categories are: education (less than HS diploma), age (greater than 30 years) and race (hispanic). Standard errors are in parentheses.

Table 4: Indebtedness and Self-efficacy

Dependent variable: Log Debt-to-Income (DTI)

	Total Debt	Credit Card Debt Vehicle Debt		Mortgage Debt
	(1)	(2)	(3)	(4)
Self Efficacy (pctile)	-0.0004** (0.0002)	-0.00001 (0.00003)	0.00004 (0.0001)	-0.0004*** (0.0001)
Observations	3,576	3,549	3,547	3,576
R-squared	0.479	0.066	0.162	0.652

Notes: Reported are OLS estimation results for regressions of log debt-to-income (by debt category) on self-efficacy and control variables. Each specification includes the full set of control variables as in the third model from Table 3. Standard errors are reported in parentheses.

*** p<0.01, ** p<0.05, * p<0.10

Table 5: Loan Delinquency and Self-efficacy, Controlling for Indebtedness

	Dependent variable: Indicator for 60+ day delinquency						
_	Credit Card Loan	Vehicle Loan	Mortgage Loan				
	(1)	(2)	(3)				
Self-efficacy (pctile)	-0.063**	-0.059*	0.003				
	(0.030)	(0.030)	(0.037)				
Log Credit Card DTI	66.8***	-5.0	-24.6				
	(11.3)	(13.6)	(18.3)				
Log Vehicle DTI	-10.1*	10.7**	5.1				
	(5.5)	(5.4)	(7.6)				
Log Mortgage DTI	2.8	-1.4	5.2**				
	(3.8)	(3.7)	(2.6)				
Observations	1,312	1,099	663				
R-squared	0.091	0.057	0.185				
Individual controls?	Y	Y	Y				

Notes: Reported are OLS estimation results for regressions of an indicator for 60+ day delinquency (by debt category) on self-efficacy, debt-to-income and the full set of individual and family covariates. Standard errors are reported in parentheses.

*** p<0.01, ** p<0.05, * p<0.10

Table 6: Self-efficacy and Delinquency, within Sibling Groups

	Credit Card		Vehic	cle Loan	Mortgage Loan		
	(1)	(2)	(3)	(4)	(5)	(6)	
Self Efficacy (pctile)	-0.151**	-0.165***	-0.127*	-0.117*	-0.050	-0.120	
	(0.061)	(0.062)	(0.065)	(0.063)	(0.123)	(0.118)	
Math (pctile)		0.069		0.071		0.190	
		(0.095)		(0.097)		(0.171)	
Reading Recog (pctile)		0.141		0.026		-0.062	
		(0.101)		(0.093)		(0.172)	
Reading Comp (pctile)		0.010		0.081		-0.099	
		(0.089)		(0.104)		(0.162)	
HS diploma		9.844		-11.116		-9.480	
		(9.554)		(6.949)		(12.195)	
Some college		2.667		-27.762***		-22.880**	
		(9.450)		(7.234)		(11.115)	
College degree		2.447		-18.739**		-8.330	
		(10.142)		(8.659)		(12.974)	
Log (HH income 2010)		-1.010		-4.668		-6.940*	
		(2.866)		(3.374)		(4.027)	
Log (mean income as add	ult)	4.816		5.153		16.725**	
		(4.984)		(5.376)		(7.370)	
Homeowner		-12.889***		-13.423***		-57.681***	
		(4.842)		(4.474)		(11.725)	
Vehicle owner		5.541				1.166	
		(5.536)				(12.535)	
Female		6.876*		6.765*		17.424***	
		(3.594)		(3.732)		(5.601)	
age 21-22		-12.178		-14.202*		-7.401	
		(10.459)		(8.422)		(13.688)	
age 23-24		-12.464		-18.343**		-28.225**	
		(9.040)		(8.224)		(12.258)	
age 25-26		-5.655		-9.025		-16.268	
		(8.552)		(7.990)		(11.617)	
age 27-28		-8.598		-4.119		-13.165	
		(7.886)		(6.895)		(9.163)	
age 29-30		-9.106		-11.439		-7.936	
		(8.681)		(7.193)		(9.197)	
Number HH members		0.645		0.641		2.973	
		(1.433)		(1.339)		(3.105)	
Married		-6.090		-1.432		-12.308	
		(4.847)		(4.470)		(8.236)	
Observations	1,383	1,351	1,134	1,109	695	679	
R-squared	0.857	0.869	0.867	0.894	0.873	0.940	
Sibling fixed effects?	Y	Y	Y	Y	Y	Y	

Notes: This table shows OLS estimation results for regressions of an indicator for 60+ day delinquency (by debt category) on self-efficacy, sibling group fixed effects and the full set of individual and family characteristics. Standard errors are in parentheses.

^{***} p<0.01, ** p<0.05, * p<0.10